Desimal: Jurnal Matematika Vol 8 No 2 (2025) 195-206

Contents lists available at DJM
DESIMAL: JURNAL MATEMATIKA
p-ISSN: 2613-9073 (print), e-ISSN: 2613-9081 (online), DOI 10.24042/djm
http://ejournal.radenintan.ac.id/index.php/desimal/index

Multi-objective vehicle routing problem with time windows via genetic algorithm

Dahlia Rizky Ketaren*, Parapat Gultom, Mahyuddin K.M. Nasution

Universitas Sumatera Utara, Indonesia

ARTICLE INFO

Article History
Received : 10-05-2025
Revised : 13-06-2025
Accepted : 13-07-2025
Published : 17-07-2025

Keywords:
Genetic Algorithm; MO-VRPTW; Optimal Route; Time Windows; Waste Transportation.

*Correspondence: E-mail:
ketaren.dahliarizky@gmail.com

Doi:
10.24042/630swz39

ABSTRACT

Efficient waste transportation requires route planning that considers time constraints, vehicle capacity, and road conditions. This study develops a Multi-Objective Vehicle Routing Problem with Time Windows model to optimize waste collection routes in Batu Bara Regency. The model simultaneously optimizes three objective functions: minimizing total travel distance, travel time, and risk based on road conditions. The solution is obtained using a Genetic Algorithm, with field data serving as model input. Simulation results show that the proposed model produces more efficient and realistic routes compared to conventional methods. The model effectively accommodates vehicle capacity constraints and customer service time windows. With the Genetic Algorithm, the solutions are not only operationally effective but also adaptable to the complex road network in the study area. These results can inform local government and waste management agencies in developing more adaptive and data-driven routing strategies, leading to cost savings, improved service efficiency, and reduced environmental impact. Moreover, the model can be extended or customized for other public logistics problems, such as food distribution or emergency response in semi-urban areas with similar infrastructure constraints. Future research can enhance this model by incorporating dynamic traffic data, multi-depot scenarios, or integrating sustainability metrics such as fuel consumption and emissions.

http://ejournal.radenintan.ac.id/index.php/desimal/index

INTRODUCTION

In an increasingly competitive era of globalization, efficiency in goods distribution and logistics management has become a critical factor for industries such as e-commerce, manufacturing, and retail. Vehicle route optimization plays a vital role in reducing operational costs while simultaneously improving the quality of customer service (Baños, Ortega, Gil, Márquez, & de Toro, 2013). One of the most widely used models in logistics management is the Vehicle Routing Problem (VRP), first introduced in 1959. This model focuses on designing vehicle routes from a central depot to serve a set of customers, with the primary objective of minimizing total cost or travel distance (Dantzig & Ramser, 1959).

Reverse logistics and closed-loop supply chains are increasingly gaining attention as sustainable strategies to manage waste, returns, and resource recovery, requiring advanced planning tools and optimization models(Govindan, Soleimani, & Kannan, 2015).

The study conducted a thorough examination of issues related to pickup and delivery, with a specific emphasis on the transportation of goods between customers and depots. Their study classified various problem types and highlighted the operational challenges and solution approaches relevant to vehicle routing with pickup and delivery constraints (Parragh, Doerner, & Hartl, 2008). Proposed a bi-objective optimization model for urban solid waste collection that uniquely incorporates visual attractiveness of the routes alongside traditional cost and efficiency metrics, offering a novel approach to routing in public service logistics (Rossit & Toncovich, 2023).

Provided a comprehensive review of recent advances in green road freight transportation, highlighting strategies to reduce environmental impact, including fuel-efficient routing and carbon emission considerations in logistics planning (Demir, Bektaş, & Laporte, 2014).

As logistics needs have grown more complex, VRP has evolved into several advanced variants. One of the most extensively studied is the Vehicle Routing Problem with Time Windows (VRPTW), which incorporates service time constraints for each customer. In VRPTW, vehicles must schedule visits within specific time windows, making it significantly more challenging than the classical VRP. The core complexity of VRPTW lies in designing optimal routes that not only achieve cost and distance efficiency but also comply with predefined time windows (Toth & Vigo, 2002).

Solving VRPTW optimally is a major challenge due to the vast size of the solution space and the high risk of getting trapped in suboptimal solutions. Linear programming and exact methods often become ineffective for large-scale problems due to computational limitations. Consequently, metaheuristic approaches have gained popularity as more flexible and efficient alternatives (Maroof, Ayvaz, & Naeem, 2024).

The NSGA-II, a fast and elitist multi-objective genetic algorithm that improves convergence speed and diversity preservation, making it one of the most widely used algorithms in multi-objective optimization problems (Deb, Pratap, Agarwal, & Meyarivan, 2002). Applied the metaheuristic technique NSGA-II to solve the multi-objective vehicle routing problem with time windows (MO-VRPTW), demonstrating that both algorithms are effective in producing diverse and high-quality Pareto-optimal solutions (Jabir, Mirjalili, & Lee, 2015).

Proposed a genetic algorithm-based approach for optimizing multi-objective supply chain networks, demonstrating the effectiveness of genetic algorithms in solving complex logistics problems (Altiparmak, Gen, Lin, & Paksoy, 2006). Conducted an in-depth analysis of genetic algorithms in multi-vehicle path optimization under time-window constraints, highlighting the advantages of integrating efficiency metrics and Pareto-based selection strategies in handling real-world scheduling problems (F. Zhang, Xie, & Zheng, 2024).

Developed a robust multi-objective optimization framework for solving the Vehicle Routing Problem with Time Windows (VRPTW), incorporating uncertainty in demand and travel times. Their approach enhances solution stability across varying scenarios by integrating robustness into the multi-objective formulation (Duan, He, & Yen, 2022).

Proposed an improved genetic algorithm tailored for the Vehicle Routing Problem with Time Windows, enhancing solution quality and convergence speed through innovative encoding and operator strategies (Wei, Qiu, Xin, & Fan, 2018).

One of the most effective metaheuristic methods for solving VRPTW is the Genetic Algorithm (GA). Genetic Algorithm is an evolutionary-based optimization technique developed by (Holland, 1975). In genetic algorithms, solutions are represented as chromosomes that undergo selection, crossover, and mutation to evolve toward better solutions in each iteration (Goldberg, 1989).

In complex logistics systems involving multiple depots and delivery constraints, demonstrated the effectiveness of genetic algorithms in solving multi-criteria pickup and delivery problems under time window and multi-vehicle conditions. Their study emphasized that GA-based approaches can handle realistic operational constraints and improve overall distribution efficiency in heterogeneous routing environments (Alaïa, Dridi, Bouchriha, & Borne, 2015).

Developed a hybrid approach combining goal programming and genetic algorithms to solve the multi-objective vehicle routing problem with time windows (MO-VRPTW). Their study emphasized the importance of addressing multiple conflicting objectives simultaneously, such as minimizing travel cost and lateness, which are common in real-world distribution systems (Ghoseiri & Ghannadpour, 2010).

Proposed a decomposition-based hybrid algorithm (MOEA/D-HGS) for the multi-objective vehicle routing problem with time windows, achieving competitive performance on standard VRPTW benchmarks by integrating efficient crossover, local search heuristics, and novel strategies for reducing vehicle count and managing infeasible solutions (Wang, Liu, & Zhang, 2023). Although the Vehicle Routing Problem with Time Windows has been widely studied in logistics and transportation management, several research gaps still remain, particularly in the context of real-world public service applications. Most previous studies have focused on optimizing single or bi-objective functions, such as minimizing distance or cost, without fully incorporating complex, real-world constraints (Wan et al., 2023).

For instance, Tan, Lee, Zhu, & Ou (2001) developed a genetic algorithm for VRPTW but focused primarily on total distance minimization, while J. Zhang, Zhao, Xue, & Li (2015) extended the objective to fuel consumption and emissions without addressing road conditions or service constraints. Moreover, few studies have utilized genetic algorithms for multi-objective VRPTW in public service contexts such as municipal waste collection or nutritional food distribution (Khan, 2022).

Although various studies have explored the Vehicle Routing Problem with Time Windows (VRPTW), most remain limited to optimizing either travel distance or time, often ignoring real-world constraints such as road conditions or strict service time windows. In particular, prior works have not simultaneously integrated travel time, distance, road condition scores, and time windows into a single optimization model (Altiparmak et al., 2006). Furthermore, although the Pareto Frontier method has been applied (Pratiwi, Nasution, & Herawati, 2023), it does not utilize evolutionary algorithms like Genetic Algorithm (GA) and omits critical constraints such as time windows, limiting practical applicability. Existing models also tend to assume ideal infrastructure, which is not representative of semi-urban or rural regions in developing countries. Therefore, this study fills these gaps by proposing a GA-based multi-objective optimization model tailored for public logistics—specifically waste transportation in Batu Bara Regency—that incorporates real-world constraints, evaluates algorithm performance, and offers scalable insights for sustainable transportation planning.

Represent VRPTW as a multi-objective problem, using a Pareto-ranking genetic algorithm that balances the number of vehicles and total distance without weight bias, demonstrating that multi-objective GA provides fair and competitive solutions in benchmark routing cases (Ombuki, Ross, & Hanshar, 2006). However, to address the complexity of the Vehicle Routing Problem with Time Windows (VRPTW), which involves multiple simultaneous objectives, they proposed a Density Restricted Genetic Algorithm (DRGA) as a multi-objective approach capable of improving both the diversity and quality of solutions. This approach demonstrates that evolutionary methods can be effectively adapted to solve logistical distribution problems with numerous constraints and conflicting objectives (García-Najera & Bullinaria, 2010).

Although the Vehicle Routing Problem with Time Windows (VRPTW) has been widely studied, most previous research still focuses on optimizing only one or two objectives, such as minimizing distance or travel time, without fully incorporating real-world complexities such as road conditions, vehicle capacity limits, and strict time windows, particularly in public service contexts. Moreover, the application of Genetic Algorithm (GA) for solving multi-objective VRPTW using real-world data remains limited, especially in semi-urban or rural areas with infrastructure challenges. This study introduces a novel approach by developing a GA-based multi-objective VRPTW model that integrates three main objectives: travel distance, travel time, and road condition scores, while also accounting for vehicle capacity constraints and service time windows. The model is applied to a real case of municipal waste transportation, offering a more adaptive, realistic, and practical solution for decision-making in public logistics under geographical and infrastructural limitations.

METHOD

This study is developmental research employing a quantitative approach through simulation and computational experiments. The focus is on solving the Multi-Objective Vehicle Routing Problem with Time Windows (VRPTW), aiming to optimize vehicle routing by considering multiple objectives such as minimizing operational costs, reducing the number of vehicles used, and ensuring compliance with customer service time windows. The research seeks to find optimal solutions for efficient distribution planning using the Genetic Algorithm (GA). The data utilized includes secondary data from a case study as well as simulated data to test the model's performance under various scenarios. The framework of the flow of thought is made in the research flowchart, which can be seen in Figure 1.

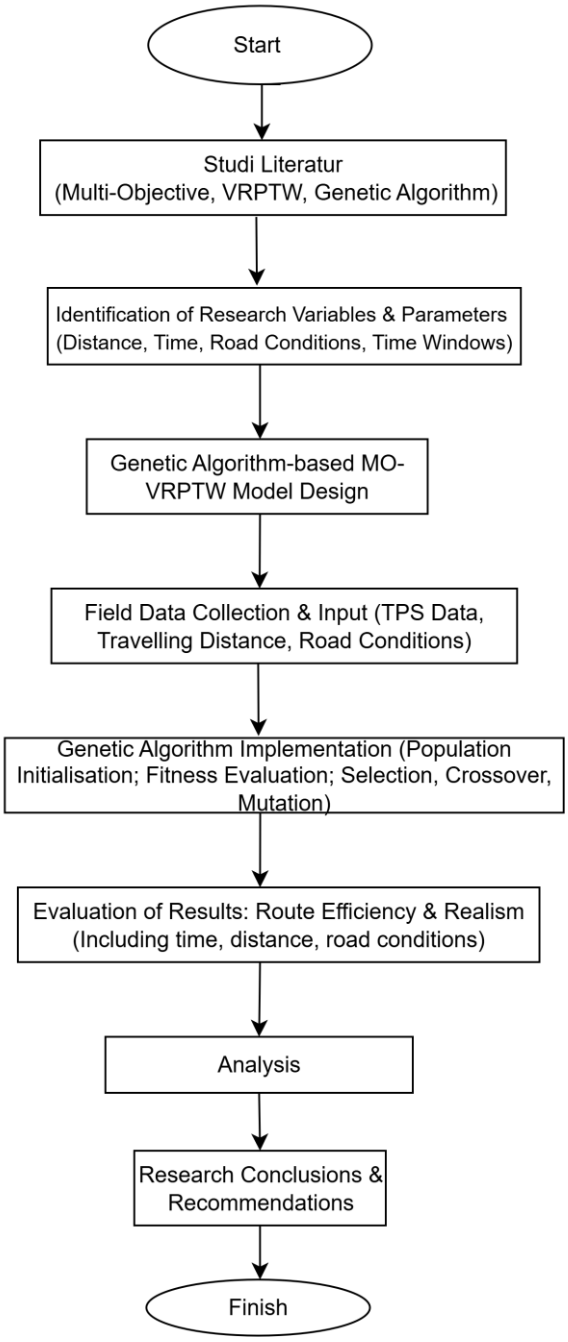

Figure 1. Reseacrh Flow Chart

This study adopts a two-stage methodological approach. First, a comprehensive literature review is conducted to collect and analyze relevant references, including scientific journals, books, and previous studies related to the Vehicle Routing Problem with Time Windows (VRPTW) and optimization using Genetic Algorithms. Second, a series of computational experiments are performed to evaluate the performance of the proposed model under various waste distribution scenarios. These experiments serve to validate the model's effectiveness in solving complex routing problems with time and capacity constraints in a real-world context.

RESULTS AND DISCUSSION

The formulation of the Multi-Objective Vehicle Routing Problem with Time Windows (MO-VRPTW) in the context of waste transportation aims to optimize vehicle routes from a single depot to multiple service points by considering vehicle capacity, service time windows, and road conditions. The model simultaneously minimizes total travel distance, travel time, and risk due to poor road conditions. Each service point is visited only once, and each vehicle must return to the depot. Since these three objectives often conflict with one another, a multi-objective optimization approach is required to produce route solutions that are efficient, timely, and reliable under complex operational conditions.

Indexes and parameters:

$i, j \in V$: Node indices, including waste collection locations

$k \in K$: Vehicle index

d_{ij} : Distance from node *i* to node *j*

t_{ij} : Travel time from node *i* to node *j*

c_{ij} : Time window at node *i* (earliest and latest allowable service time)

$[e_i, l_i]$: time window di titik i

s_i : Service time at node *i*

Q_k : Maximum capacity of vehicle *k*

q_i : Amount of waste to be collected at node *i*

a_i : Arrival time of the vehicle at node *i*

v_i : Maximum number of visits allowed to node *i*

Variabel Keputusan

$$x_{ijk} = \begin{cases} 1, \textit{if vehicle k travels from node i to node j} \\ 0, \text{otherwise} \end{cases}$$

a_{ik} : Arrival time of the vehicle at node i

u_{ik} : Cumulative load of the vehicle after servicing node i

Objective Functions

1. Minimization of Total Travel Distance
   Minimize the total distance traveled to reduce fuel consumption, operational costs, and environmental impact.
   $$f_1 = \Sigma\Sigma\Sigma\, d_{ij} \cdot x_{ij}^k$$
2. Minimization of Total Travel Time
   Reduce the overall travel duration and ensure arrivals fall within the specified time windows.
   $$f_2 = \Sigma\Sigma\Sigma\, t_{ij} \cdot x_{ij}^k$$
3. Minimization of Road Risk (Poor Conditions)
   Avoid routes with poor road conditions to prevent vehicle damage and delays.
   $$f_3 = \Sigma\Sigma\Sigma\, r_{ij} \cdot x_{ij}^k$$
4. Combined Objective (Weighted Sum)
   If a weighted sum approach is used:
   $$f = w_1 \cdot f_1 + w_2 \cdot f_2 + w_3 \cdot f_3$$

Where:
w_1: weight for travel distance
w_2: weight for travel time
w_3: weight for road condition risk

Constraint Functions

1. Maximum Visit per Node
   Each service point can be visited at most mim_imi times:
   $\Sigma_k \Sigma_j x_{ij}^k \le m_i$
2. Flow Conservation
   A vehicle that arrives at a node must also depart from it:
   $\Sigma_j x_{ij}^k = \Sigma_j x_{ji}^k$
3. Start and End at the Depot
   Each vehicle must start from and return to the depot.
4. Vehicle Capacity Constraint
   The load of each vehicle must not exceed its capacity:
   $$Q_i \le q_k$$
5. Service Time Windows
   Vehicles must arrive at node iii within the allowed time window:
   $e_i \le a_i \le l_i$
   $a_j \ge a_i + s_i + t_{ij} - M(1 - x_{ij}^k)$

In the implementation of the Genetic Algorithm for solving the MO-VRPTW in the context of waste transportation in Batu Bara Regency, ten waste collection points (TPS) are considered, each with specific time windows and varying travel times between the depot and TPS, as well as between TPS themselves. Table 1 presents the customer data, including the node, sub-district name, and waste volume in tons.

Table 1. Costumer Data

Node	Sub-district	Volume (Ton)
P1	Madang Deras	6
P2	Laut Tador	4.5
P3	Sei Suka	10
P4	Air Putih	12
P5	Lima Puluh Kota	8
P6	Datuk LP	2
P7	Talawi	4.5
P8	Sei Balai	4.5
P9	Tanjung Tiram	15
P10	LP Pesisir	2.5

Table 1 presents data on customer nodes in the context of waste collection routes across various sub-districts (*kecamatan*) in the study area. Each node (P1–P10) represents a location (TPS or service point) with an associated sub-district and waste volume to be collected. The volume is measured in tons and reflects the total waste demand at each location.

These values are crucial for route optimization, especially when considering vehicle capacity constraints and time windows in the VRPTW model.

In the manual calculation, the initial population size (popSize) is set to 10. The chromosome length corresponds to the number of destinations to be visited, with all routes starting from the depot at 07:00 AM. Each vehicle has a uniform capacity of 4 tons and is assumed to travel at a constant speed of 30 km/h. Table 2 presents the travel distance data between nodes.

Table 2. Distance Travelled Data

	Distance Travelled Data (km)									
s	P I	P II	P III	P IV	P V	P VI	P VII	P VIII	P IX	P X
P I	0	27	20.1	26.2	44.2	42	42.5	54.5	40.6	27.8
P II	27	0	9.6	14.6	40.9	38.1	49.6	59.9	51.5	54.8
P III	20.1	9.6	0	5	23	28.5	40	45.5	41.9	47.9
P IV	26.2	14.6	5	0	18	23.5	35	40.5	36.9	49.7
P V	44.2	40.9	23	18	0	9.7	21.2	19	23.1	35.9
P VI	42	38.1	28.5	23.5	9.7	0	11.5	17	13.4	26.2
P VII	42.5	49.6	40	35	21.2	11.5	0	12	1.9	14.7
P VIII	54.5	59.9	45.5	40.5	19	17	12	0	15.5	26.7
P IX	40.6	51.5	41.9	36.9	23.1	13.4	1.9	15.5	0	12.8
P X	27.8	54.8	47.9	49.7	35.9	26.2	14.7	26.7	12.8	0

Table 2 presents the Distance Travelled Data matrix between 10 service points (P1 to P10), representing the travel distance in kilometers between each node pair. The diagonal entries are zero (0), indicating no distance between a node and itself. The matrix is symmetric, meaning the distance from Pi to Pj is equal to the distance from Pj to Pi.

The values range from as low as 0 km (same node) to a maximum of approximately 59.9 km (e.g., from P2 to P VIII). These distances are essential input for solving the Vehicle Routing Problem with Time Windows (VRPTW), as they directly affect route cost, time calculation, and optimization strategies.

Each trip has a different travel time depending on the route taken. Vehicle trips will be penalized if the vehicle's arrival time is more than the ideal final visit time.

Process of Genetic Algorithm in MO-VRPTW

1. Individual
   An individual represents a single candidate solution within the population. In the context of VRP, an individual corresponds to one possible waste collection route solution involving all vehicles.
2. Chromosome
   A chromosome is the representation of an individual in the form of a sequence of nodes that each vehicle must visit. can be a chromosome. In VRPTW, a chromosome may also include the division of routes among multiple vehicles.
3. Travel Penalty
   A travel penalty is a penalty value applied during fitness calculation if a solution violates:
   1) Vehicle capacity constraints, or
   2) Time window constraints. The purpose of the penalty is to discourage infeasible solutions from being selected.
4. Fitness
   Fitness is the evaluation value of a solution's quality. In an MO-VRPTW problem, the fitness score is often based on a combination of:
   1) Total travel distance
   2) Total travel time
   3) Road condition scores
   4) Plus penalties for any constraint violations

The lower the total fitness value (in a minimization problem), the better the solution.

After the penalty result and the total travel time are known, the next stage is to calculate the fitness of each individual. The fitness value is obtained from the calculation of each individual. The results of the fitness calculation can be seen in Table 3. The fitness calculation for individual P1 is as follows:

$$P1 = \frac{1}{1869 + 636} = 0.000399$$

After the crossover and mutation reproduction process is carried out, the next step is the selection process. The method used in the selection process is the roulette wheel. The calculation of fitness values, probability, and cumulative probability is stated in the equation.

Table 3. Fitness Calculation

Individual	Chromoshome	Travel Penalty	Distance	Fitness
P1	76123458	1869	636	0.000399
P2	87456123	1195	550	0.000573
P3	12345678	2792	544	0.000300
P4	56781234	2006	556	0.000390
P5	82345617	678	573	0.000799
P6	23456781	631	567	0.000835
P7	56781234	2006	556	0.000390
P8	34561278	861	587	0.000691
P9	45678123	1351	588	0.000516
P10	67812345	2365	670	0.000329

Table 3 presents the fitness evaluation results for 10 individuals (P1–P10) generated during the Genetic Algorithm (GA) process in solving the Vehicle Routing Problem with Time Windows (VRPTW). Each individual represents a possible route solution encoded as a chromosome.

$$prob_k = \frac{fitness(P_k)}{total\_fitness}$$

$$probCum_k = \sum_{j=1}^{k} prob_j$$

The calculation of probability and cumulative probability on individual P1 is as follows:

$$prob_{p1} = \frac{0.000399}{0.0007797} = 0.051202$$

$$probCum_{p1} = 0 + 0.051202 = 0.051202$$

$$probCum_{p2} = 0.051202 + 0.073501 = 0.124703$$

After getting the fitness value of each individual, then the 10 best individuals are selected based on the highest fitness value. By using a roulette wheel to generate a random interval value [0,1]. Then select the value of "k" as the selected individual where the value $probCum_{k-1}$ < $random \leq probCum_k$.

Table 4. individual as winner

Individual	Chromoshome	k	Individu	Fitness
P1	0.703993	11	P11	0.000300
P2	0.812046	14	P14	0.000435
P3	0.169125	4	p4	0.000390
P4	0.585947	9	p9	0.000516
P5	0.781151	13	p13	0.000408
P6	0.970429	16	p16	0.000794
P7	0.341632	6	p6	**0.000835**
P8	0.879543	15	p15	0.000288
P9	0.131532	3	P3	0.000300
P10	0.585354	9	P9	0.000516

Table 4 presents a summary of selected individuals in the Genetic Algorithm (GA) process, highlighting their chromosome fitness values and selection outcomes. The table helps identify the best-performing solutions (or "winners") based on fitness evaluation. The best fitness in the table is achieved by individual P6 with a fitness value of 0.000835, highlighted in yellow—suggesting it was the most optimal solution in this set. Chromosome values vary between 0.16 and 0.97, possibly indicating selection probabilities or scores before crossover. Fitness scores range from 0.000288 (P15) to 0.000835 (P6)—showing variance in solution quality across the individuals.

CONCLUSIONS AND SUGGESTIONS

This study successfully developed a Multi-Objective Vehicle Routing Problem with Time Windows (MO-VRPTW) model for waste transportation, considering three main objectives: minimizing travel distance, travel time, and road condition risks. The model effectively represents real-world challenges, such as vehicle capacity limitations and service time constraints. By applying a Genetic Algorithm (GA), efficient and near-optimal route solutions were obtained. The optimal result was achieved with a population size of 10, 100 generations, and parameters Cr = 0.4 and Mr = 0.2, yielding an average fitness value of 0.000835. The optimization results indicate potential reductions in operational time and improvements in efficiency and transportation safety.

In the future, the model can be enhanced to better adapt to field uncertainties, such as fluctuations in waste volume and traffic conditions, and expanded to include social impacts, local stakeholder participation, and overall system sustainability.

REFERENCES

Alaïa, E. Ben, Dridi, I. H., Bouchriha, H., & Borne, P. (2015). Genetic algorithm for multi-criteria optimization of multi-depots pick-up and delivery problems with time windows and multi-vehicles. *Acta Polytechnica Hungarica*, *12*(8). https://doi.org/10.12700/APH.12.8.2015.8.9

Altiparmak, F., Gen, M., Lin, L., & Paksoy, T. (2006). A genetic algorithm approach for multi-objective optimization of supply chain networks. *Computers & Industrial Engineering*, *51*(1), 196–215. https://doi.org/10.1016/j.cie.2006.07.011

Baños, R., Ortega, J., Gil, C., Márquez, A. L., & de Toro, F. (2013). A hybrid metaheuristic for multi-objective vehicle routing problems with time windows. *Computers & Industrial Engineering*, *65*(2), 286–296. https://doi.org/10.1016/j.cie.2013.01.007

Dantzig, G. B., & Ramser, J. H. (1959). The truck dispatching problem. *Management Science*, *6*(1). https://doi.org/10.1287/mnsc.6.1.80

Deb, K., Pratap, A., Agarwal, S., & Meyarivan, T. (2002). A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE Transactions on Evolutionary Computation*, *6*(2), 182–197. https://doi.org/10.1109/4235.996017

Demir, E., Bektaş, T., & Laporte, G. (2014). A review of recent research on green road freight transportation. *European Journal of Operational Research*, *237*(3), 775–793. https://doi.org/10.1016/j.ejor.2013.12.033

Duan, J., He, Z., & Yen, G. G. (2022). Robust multiobjective optimization for vehicle routing problem with time windows. *IEEE Transactions on Cybernetics*, *52*(8), 8300–8314. https://doi.org/10.1109/TCYB.2021.3049635

García-Najera, A., & Bullinaria, J. A. (2010). Optimizing delivery time in multi-objective vehicle routing problems with time windows. In *Parallel Problem Solving from Nature, PPSN XI* (pp. 51–60). Berlin, Heidelberg: Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-15871-1_6

Ghoseiri, K., & Ghannadpour, S. F. (2010). Multi-objective vehicle routing problem with time windows using goal programming and genetic algorithm. *Applied Soft Computing*, *10*(4), 1096–1107. https://doi.org/10.1016/j.asoc.2010.04.001

Goldberg, D. E. (1989). *Genetic algorithms in search, optimization, and machine learning*. Addison-Wesley.

Govindan, K., Soleimani, H., & Kannan, D. (2015). Reverse logistics and closed-loop supply chain: A comprehensive review to explore the future. *European Journal of Operational Research*, Vol. 240. https://doi.org/10.1016/j.ejor.2014.07.012

Holland, J. H. (1975). Adaptation in natural and artificial systems: An introductory analysis with applications to biology, control, and artificial intelligence. In *Ann Arbor University of Michigan Press 1975*.

Jabir, E., Mirjalili, S., & Lee, M. (2015). Solving multi-objective vehicle routing problem with time windows using NSGA-II and MOPSO. *Applied Soft Computing*, *47*, 577–590.

Khan, A. S. (2022). Multi-objective optimization of a cost-effective modular reconfigurable manufacturing system: An integration of product quality and vehicle routing problem. *IEEE Access*, *10*, 5304–5326. https://doi.org/10.1109/ACCESS.2021.3137563

Maroof, A., Ayvaz, B., & Naeem, K. (2024). Logistics optimization using hybrid genetic algorithm (hga): A solution to the vehicle routing problem with time windows (vrptw). *IEEE Access*, *12*, 36974–36989. https://doi.org/10.1109/ACCESS.2024.3373699

Ombuki, B., Ross, B. J., & Hanshar, F. (2006). Multi-objective genetic algorithms for vehicle routing problem with time windows. *Applied Intelligence*, *24*(1), 17–30. https://doi.org/10.1007/s10489-006-6926-z

Parragh, S. N., Doerner, K. F., & Hartl, R. F. (2008). A survey on pickup and delivery problems: Part I: Transportation between customers and depot. *Journal Fur Betriebswirtschaft*, *58*(1).

Pratiwi, A., Nasution, M. K. M., & Herawati, E. (2023). Pareto frontier approach to determining the optimal path on multi-objectives. *Sinkron*, *8*(3). https://doi.org/10.33395/sinkron.v8i3.12465

Rossit, D., & Toncovich, A. (2023). Bi-objective optimization of a VRP problem applied to urban solid waste collection through a model that includes the visual attraction of routes. *XXI SEPROSUL – Semana de Engenharia de Produção e Mecânica Sulamericana*.

Tan, K. C., Lee, L. H., Zhu, Q. L., & Ou, K. (2001). Heuristic methods for vehicle routing problem with time windows. *Artificial Intelligence in Engineering*, *15*(3). https://doi.org/10.1016/S0954-1810(01)00005-X

Toth, P., & Vigo, D. (2002). The vehicle routing problem. *Society for Industrial and Applied Mathematics (SIAM)*.

Wan, H., Ma, J., Yu, Q., Sun, G., He, H., & Li, H. (2023). Modeling and optimization of multi-model waste vehicle routing problem based on the time window. *Journal of Database Management*, *34*(3), 1–16. https://doi.org/10.4018/JDM.321543

Wang, Y., Liu, F., & Zhang, Q. (2023). A decomposition-based hybrid algorithm for multi-objective vehicle routing problem with time windows. *2023 IEEE Congress on Evolutionary Computation (CEC)*, 1–8. IEEE. https://doi.org/10.1109/CEC53210.2023.10254116

Wei, C., Qiu, C., Xin, Q., & Fan, Z. (2018, April 12). *An improved genetic algorithm for vehicle routing problem with time windows*. https://doi.org/10.20944/preprints201804.0169.v1

Zhang, F., Xie, Y., & Zheng, L. (2024). Application and efficiency analysis of genetic algorithm in multi-vehicle path optimisation models under time window constraints. *2024 IEEE 7th International Conference on Information Systems and Computer Aided Education (ICISCAE)*, 938–944. IEEE. https://doi.org/10.1109/ICISCAE62304.2024.10761568

Zhang, J., Zhao, Y., Xue, W., & Li, J. (2015). Vehicle routing problem with fuel consumption and carbon emission. *International Journal of Production Economics*, *170*, 234–242. https://doi.org/10.1016/j.ijpe.2015.09.031